

Bitcoin price forecasting using hybrid genetic algorithm

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Abstract: The hybrid genetic algorithm is a method that combines the principles of genetic algorithms with other optimization techniques to improve the efficiency and effectiveness of the optimization process. By integrating genetic algorithms with other algorithms or heuristics, the hybrid approach can leverage the strengths of each method to find better solutions in a shorter amount of time. This combination allows for a more robust and adaptable optimization process, leading to improved results in various problem-solving scenarios.

Bitcoin and digital currencies have emerged as a new market for investment. Therefore, the prediction of their future trend and prices is highly significant. In this research, the factors influencing the price of bitcoin were identified and extracted based on previous researches. The identified factors include the US dollar index, CPI index, S&P 500, Dow Jones, and gold price. Considering the performance of metaheuristic algorithms in predicting bitcoin price, this research utilized genetic algorithm and particle swarm optimization algorithm, and proposed a hybrid algorithm to improve their performance.

According to our results, among the investigated factors, the US dollar index has the greatest impact on bitcoin price, followed by inflation rate and the CPI index. Additionally, the proposed hybrid algorithm outperforms the particle swarm optimization and genetic algorithms, with a prediction error of 7.3%. It should be noted that the type and magnitude of the impact of the investigated factors may change over time. For example, a factor that previously had a direct impact may become reversed or neutralized over time.

Keywords: Bitcoin; Genetic algorithm; Particle swarm optimization; Hybrid; Prediction

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1 Introduction

Recently, digital currencies and Bitcoin have become major topics in the financial industry. Cryptocurrency is a virtual currency that utilizes encryption for security purposes, making counterfeiting a digital currency difficult. The most attractive and defining characteristic of digital currency is its organic nature; it is not issued by any central authority and is theoretically immune to government intervention or manipulation [3].

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The first digital currency, Bitcoin, was created in 2009 and is now the king of the digital currency world. Bitcoin can be anti-inflationary because the total number of coins available for this currency is limited to 21 million. Digital currencies represent a significant revolution in transactions and have dramatically transformed global transactions around the world [2].

Predicting the future of Bitcoin is important, as it has become a concern for many investors. Despite the relative novelty of the digital currency market, it has shown significant growth in the financial markets over the past few years, with the market volume currently approaching one trillion dollars. Therefore, predicting this market can be of great significance. In this study, we aimed to identify the factors that influence the price of Bitcoin and predict its future price using genetic algorithms and particle swarm optimization. We aim to find a pattern for predicting the price of Bitcoin, which is a concern for most investors, so that investors can confidently invest in digital currencies based on this pattern. To achieve this, we will utilize metaheuristic methods such as genetic algorithms and particle swarm optimization. The reason for using particle swarm optimization is its advantages, including memory utilization, collaboration and information sharing among particles, and ease of implementation and execution. Additionally, genetic algorithms have high search capabilities and can overcome the issue of particle swarm optimization, which may get trapped in local optima. The combination of these two algorithms can provide an optimal solution and good predictions [1,16,19,27].

2 Theoretical Foundations and Research Background

In 2020, Gill conducted research using deep learning algorithms and concluded that the price of Bitcoin does not follow the hypothesis of a random walk and efficient market and can be predicted [5]. In a study conducted by Tian and colleagues in 2018, they examined the fluctuations of Bitcoin based on buying and selling orders and concluded that buying and selling orders have a close correlation with market fluctuations [8].

In a research conducted by Dr. Seyed Amir Hossein Manjami and colleagues in 2009, they aimed to predict stocks using a fuzzy neural network combined with a genetic algorithm. They compared this model with an artificial neural network and concluded that the hybrid model of the fuzzy neural network with the genetic algorithm had more accurate and robust predictions compared to the artificial neural network [18].

In a research conducted by Sharifi and colleagues in 2021, they attempted to predict the price of Bitcoin using a combined model of ARIMA (Autoregressive Integrated Moving Average) and deep learning. The results showed that the ARIMA-GRU (Gated Recurrent Unit) model outperformed other models in terms of evaluation metrics [26]. Mohammad and Youssef demonstrated in a research study in 2021 that the gated recurrent unit (GRU) architecture outperforms short-term memory models, long short-term memory (LSTM) models, and bidirectional LSTM (bi-LSTM) models in predicting all digital currencies [9].

Kaveh Khalili and colleagues used a combination of the ARIMA model and three types of deep neural networks, including RNN, LSTM, and GRU, to predict the price of Bitcoin in a research study. The main objective of this study was to determine the impact of deep learning models on the performance of future Bitcoin price predictions. In the proposed model, the linear components in the dataset were first separated using ARIMA, and the resulting residuals were separately transferred to each of the neural networks. The results showed that the GRU-ARIMA model had better results in evaluation metrics compared to other models [17].

Faqih Mohammadi and colleagues conducted a research study in 2020 using the grey system theory and concluded that it is possible to predict the price of Bitcoin within a 5-day time window. They achieved an average error of 1.14% using the GM (1,1) model [7]. In 2018, Takahiro showed that asymmetric volatility models such as EGARCH and APARCH have more predictive power, and the normal distribution is more likely to be consistent with Bitcoin data [10]. Pongodi and colleagues also conducted a research study in 2020 using the ARIMA model and concluded that factors such as total Bitcoin transactions, trading volume, current Bitcoin price, and market

capitalization have the greatest impact on the price of Bitcoin. Additionally, the results obtained in this model were similar to the results obtained in the past using neural networks [23].

Mohammad Hassan and colleagues conducted a research study in 2019 comparing the ARIMA and NNAR models. In their first experimental sample, they found that ARIMA performed better. However, in their second experimental sample, they concluded that NNAR was superior. The results may indicate that the performance of these models can vary depending on the specific dataset or time period being analyzed [21]. Patrick and his colleague concluded in a research they conducted in 2020 that the LSTM method provides a relatively accurate prediction for the price of Bitcoin the next day [15]. A research study in 2020 showed that using the fuzzy cuckoo search algorithm and deep LSTM for predicting Bitcoin prices, the fuzzy cuckoo search algorithm had the lowest error and highest accuracy compared to non-fuzzy approaches [24]. The results of a study indicated that Bitcoin returns exhibit non-constant conditional variance, which can be interpreted as a profitable bubble [6]. In a research conducted by Sanchez and Garcia, it was stated that Elliot waves can provide relatively accurate predictions without exception for a certain period of time [25]. In a research conducted in 2017, the variables of Consumer Price Index (CPI) for all urban consumers, Dow Jones Industrial Average (DJIA), US Dollar Index (USDI), Effective Federal Funds Rate (FFR), and gold price were selected to investigate the relationship between gold and Bitcoin prices. By using the VEC model, the results showed that economic factors such as CPI, DJIA, FFR, and USDI have a long-term negative impact on Bitcoin prices. However, the price of gold does not have a long-term effect on Bitcoin prices [30].

In 2023, researchers attempted to predict the price of Bitcoin using the random forest regression machine learning method. They concluded that this prediction can be useful for the following day if the price of Bitcoin exhibits relative stability [4]. Shengo and his colleagues in 2022 utilized an integrated deep learning approach to predict the price of Bitcoin. The objective of this method was to consider various external and internal factors that influence the price of Bitcoin. In their research, they found that the proposed method for predicting the price of Bitcoin is promising and superior compared to other methods [29]. In 2020, Maleki and his colleagues used deep learning to predict the price of Bitcoin based on three other popular cryptocurrencies: Ethereum, Ripple, and Litecoin. They ultimately concluded that Ripple (XRP) outperformed the others in predicting the price of Bitcoin more accurately [14]. In 2022, Naghipour and his colleagues focused on using neural networks to predict Bitcoin prices. Through their research, they found that neural networks perform well in forecasting the time series of Bitcoin prices and explaining its high fluctuations [22]. In 2021, Moxi Li used the Markov method to predict Bitcoin prices and ultimately concluded that the Markov method has lower error rates compared to other traditional methods and machine learning for short-term predictions [13]. In 2020, Jiang utilized deep learning techniques to predict Bitcoin prices and compared different models. Ultimately, he concluded that the MLP method was not suitable for accurate predictions, while the LSTM method showed better performance [11]. In 2022, Wardak and Rashid conducted a study that concluded that the LSTM method performs better than other methods in accurately predicting short-term Bitcoin price movements [28]. In 2020, Khodami and colleagues conducted predictions using various methods, including ARIMA, machine learning, artificial neural networks, Bayesian methods, Support Vector Machine (SVM), and Random Forest. Ultimately, they concluded that the ARIMA and Bayesian approaches outperformed the others in terms of performance [12]. Based on previous studies on Bitcoin price prediction, it can be concluded that deep learning methods and neural networks are relatively effective in short-term predictions and perform better than other methods. However, no study has been conducted on the combined impact of factors affecting Bitcoin prices, and none of the studies have used metaheuristic algorithms such as genetic algorithms and particle swarm optimization. Therefore, we have decided to investigate the factors affecting Bitcoin prices and use metaheuristic algorithms for prediction [20]. In this study, our approach is fundamental because the price of Bitcoin changes with the

release of news. In fact, technical analysis is not reliable for prediction in this market because the release of positive or negative news about Bitcoin can neutralize all technical analyses.

3 Research Methodology

In this research, two main categories of heuristic are taken into account to reach a hybrid one; particle swarm optimization and genetic algorithm. At the following we describe each one in brief.

3.1 Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) method was introduced in 1995 by James Kennedy and Russell Eberhart with the aim of creating a form of computational intelligence that did not rely solely on individual capabilities, but instead drew inspiration from social models and existing social relationships. Their work led to the development of a powerful optimization algorithm called Particle Swarm Optimization or PSO, which is inspired by the collective behavior of groups of animals such as birds and fish. Inspired by evolved behaviors in nature, researchers have adopted two properties from animals: responsiveness to the environment and self-organization. The Particle Swarm Optimization algorithm moves particles towards the best solution found in the past so that they can find a better solution than the previous one. The movement of each particle is based on factors such as cognitive factor, social factor, and inertia. According to the cognitive factor, each particle bases its future movement on the path it has taken in the past. The social factor utilizes the experiences of other particles in the group, and the inertia factor is the tendency of the particle to maintain its previous direction.

3.2 Genetic Algorithm

Every organism living in an environment must be able to adapt itself to the environment, a process known as evolution. Evolution arises from phenomena such as natural selection, reproduction, mutation, and coexistence. The organisms we currently observe in nature have fully adapted and aligned themselves with their surroundings.

The genetic algorithm (GA) is a type of evolutionary algorithm that utilizes biological techniques such as inheritance and mutation to find optimal solutions. It was invented by John Holland in 1975. The algorithm performs random optimization by randomly selecting a population, and generations continue in this manner. Each generation is evaluated based on its fitness, and the best solutions are selected.

Each living organism has a unique DNA structure, establishing a one-to-one relationship between the organism and its genetic sequence. This uniqueness holds even among individuals of the same species, with no repetition. However, some simple single-celled organisms may be exceptions to this rule. This relationship is referred to as coding, where each living organism can be considered as primary information, and its DNA sequence acts as the code.

Current organisms are the result of thousands of iterations of an optimization algorithm aimed at increasing their survival capabilities. By mimicking the natural methods used to improve living organisms, we can optimize our own processes. In optimization, we seek to find the best solution among multiple possibilities for a problem.

3.3 Genetic Algorithm and Particle Swarm Optimization Combination

By studying the applications of various artificial intelligence algorithms, it has been determined that each algorithm has its strengths and weaknesses. Therefore, by identifying the strengths and weaknesses of these

algorithms, we can combine them in a way that leverages their strengths and mitigates their weaknesses, ultimately achieving a more efficient algorithm.

In the Particle Swarm Optimization algorithm, rapid convergence can sometimes result in getting stuck in a local optimal solution. To address this issue and avoid being trapped in a local optimum, another algorithm with high search power is needed. In this research, we utilized the Genetic Algorithm, known for its high search power, to complement the Particle Swarm Optimization algorithm and reduce the likelihood of getting stuck in a local optimal solution.

3.4 Research conceptual model

To predict the price of commodities, stocks, or digital currencies like Bitcoin, it is important to identify and utilize the factors that influence their prices. In this study, our focus is on predicting the price of Bitcoin, and as such, we have identified several key factors that have been found to be influential in its price. We have drawn upon previous studies to determine these factors, which include:

1. Gold price
2. Dollar index
3. Consumer index
4. Inflation rate
5. Dow Jones index
6. S&P 500 index

The conceptual model is described in figure 1.

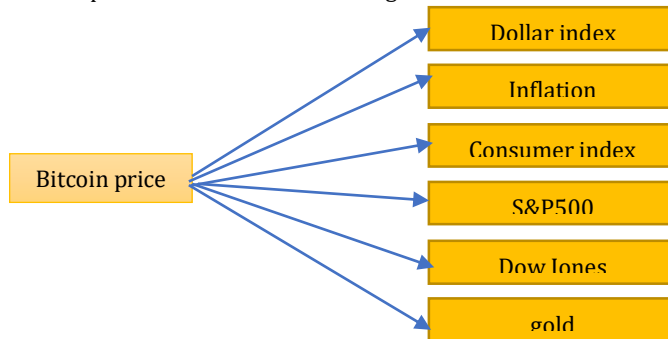


Figure 1. Conceptual model of research

For the purpose of this research, historical price data for all factors and Bitcoin is required. We have collected this data from reputable websites. Bitcoin has been available since 2009, and we have extracted data for each month, considering the closing price at the end of that month. This data will be used to make predictions using the particle swarm algorithm, the genetic algorithm, and a combination of both. The results from these algorithms will be compared. Three scenarios will be considered in this study: predicting the price of Bitcoin using the particle swarm algorithm, the genetic algorithm, and a combination of both.

Objective Function Definition: In this section, our focus is on defining the objective function. Six factors have been identified as influential on the price of Bitcoin, with each factor having a specific coefficient that impacts Bitcoin. Some factors are more significant than others. To make predictions, we must first determine the importance of these factors and incorporate them into the objective function.

We can express the Mean Squared Error (MSE) as a function that needs to be minimized. The goal is to minimize the MSE by adjusting the coefficients $a_1, a_2, a_3, a_4, a_5,$ and a_6 in the equation $\hat{y} = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6$. The minimization form can be written as finding the values of $a_1, a_2, a_3, a_4, a_5,$ and a_6 that minimize the MSE. This can be represented as:

$$\text{Minimize: } \text{MSE} = 1/n * \sum_{(i=1 \text{ to } n)} (Y_i - \hat{Y}_i)^2 \quad (3-1)$$

$$e = y - \hat{y} \quad (3-2)$$

$$\text{Subject to: } \hat{y} = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 \quad (3-3)$$

The objective is to find the values of $a_1, a_2, a_3, a_4, a_5,$ and a_6 that minimize the MSE while satisfying the relationship between the predicted output (\hat{y}) and the input variables ($x_1, x_2, x_3, x_4, x_5, x_6$). This optimization problem aims to improve the accuracy of the predictive model by minimizing the error between the actual and predicted values.

The variables $x_1, x_2, x_3, x_4, x_5,$ and x_6 are the input variables, and $a_1, a_2, a_3, a_4, a_5,$ and a_6 are the coefficients that weigh the importance of each input variable in predicting the output. The X 's represent the influential factors on the price of Bitcoin, factors include the US dollar index, CPI index, S&P 500, Dow Jones, and gold price. The a 's represent the weighting coefficients assigned to each factor. Y represents the actual price of Bitcoin, and \hat{y} represents the set of obtained solutions, which should have a minimum difference from Y .

4 Data Analysis and Findings

The data used in this research was collected from reputable global websites. Table 1 includes a list of websites from which historical price data for each influential factor on Bitcoin and Bitcoin itself was extracted. This table includes the names of variables (factors affecting the price of Bitcoin), the defined symbol for each variable, and the websites from which the data was extracted. To ensure that the data was comparable on the same scale, we normalized it before using it.

Table 1. List of information collection sites

Variable	Variable name	site
x1	index dollar	https://www.investing.com/indices/usdollar-historical-data
x2	Inflation Rates and CPI	https://www.rateinflation.com/
x3	Historical CPI for United State	https://www.rateinflation.com/consumer-price-index/usa-historical-cpi/
x4	S&P 500 Index	https://finance.yahoo.com/quote/%5EGSPC/history?period1=1230768000&period2=1672617600&interval=1mo&filter=history&frequency=1mo&includeAdjustedClose=true
x5	Dow Jones Industrial Average	https://finance.yahoo.com/quote/%5EDJI/history?period1=1230854400&period2=1672617600&interval=1mo&filter=history&frequency=1mo&includeAdjustedClose=true

x6	Gold	https://finance.yahoo.com/quote/GC%3DF/history?period1=1230768000&period2=1672617600&interval=1mo&filter=history&frequency=1mo&includeAdjustedClose=true
Y	BTC price	https://finance.yahoo.com/quote/BTC-USD/history?period1=1230768000&period2=1672617600&interval=1mo&filter=history&frequency=1mo&includeAdjustedClose=true

Table 2 presents the variables and the optimized coefficients obtained for the objective function using the Particle Swarm Optimization (PSO) algorithm, Genetic Algorithm (GA), and a combination of both algorithms.

Table 2. Optimum coefficients of variables with different training methods

Variable name	Optimal coefficients with particle swarm algorithm	Optimal coefficients with genetic algorithm	Optimal coefficients by combining two algorithms	Average optimal coefficients
index Doller	-2.74	-2.27	-4.90	-4.56
Inflation Rates	2.14	0.93	4.79	4.06
Historical CPI for United State	1.14	2.77	2.15	2.27
S&P 500 Index	0.01	0.6	-2.47	-1.55
Dow Jones Industrial	-0.36	-0.64	0.55	0.14
Gold	0.55	0.06	-0.03	0.05

Each coefficient in Table 2 represents the significance of the corresponding variable in influencing the price of Bitcoin. These coefficients vary across different methods, so the optimal coefficient for influential factors is determined as the average among all three methods, as shown in Table 2. For instance, the Dollar Index demonstrates an inverse relationship with the price of Bitcoin. Whenever the Dollar Index increases, the price of Bitcoin tends to decrease, and vice versa.

In the Particle Swarm Optimization algorithm, the objective function aims to minimize the average of squared errors. The smaller the errors, the better the model performs, and the more optimal solution is obtained. The objective function minimizes the disparity between the actual Bitcoin price and the estimated price derived from the model (initial solutions of the algorithm). In the Particle Swarm Optimization method, the inertia coefficient is set to 1, and both the personal and social learning coefficients are set to 2. To enhance the results, we mitigate the inertia coefficient by applying a damping factor of 0.99 in this algorithm. The execution parameters of the program are outlined in Table 3.

Table 3. Particle swarm algorithm parameters of the training period

nvar ¹¹	varmin ¹⁰	varmax ⁹	Npop ⁸	w ⁷	wdamp ⁶	C1&C2 ⁵
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⁵ Personal Learning Coefficient & Global Learning Coefficient

⁶ Inertia Weight Damping Ratio

⁷ Inertia Weight

⁸ Swarm (Population) Size

⁹ Upper Bound of Variables

¹⁰ Lower Bound of Variables

¹¹ Number of Variables

6	-10	+10	200	1	0.99	2
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Table 4. Average, maximum and minimum errors in the particle swarm algorithm of the training course

Mean squared error (Dollar)		
Max	Average	Min
0.0107	0.0113	0.0098

Table 4 displays the maximum, minimum, and average errors obtained through the Particle Swarm Optimization algorithm.

Table 5 showcases the mean squared errors achieved using the Particle Swarm Optimization (PSO) method for 0.0103. As indicated in Table 5, with 300 iterations and 120700 function evaluations, the mean squared error of 0.0103 was obtained.

Table 5. Results by using PSO of the training period

Iteration	NFE ¹²	Mean squared error (Dollar)
300	120700	0.0103

Figure 2 illustrates the optimal contribution in bridging the gap between y and \hat{y} .

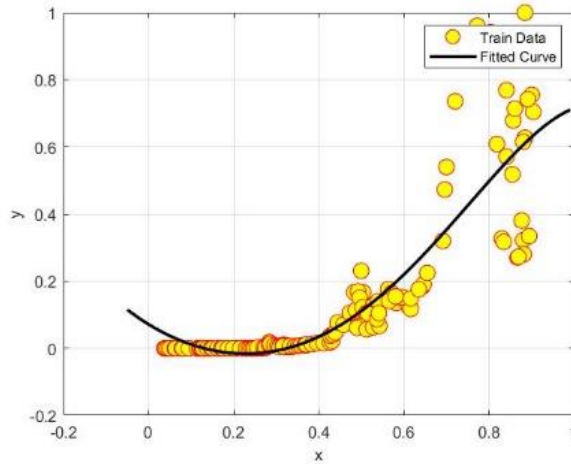


Figure 2. Error contribution in particle swarm algorithm

Figure 3 displays the number of function evaluations on the x-axis and the mean squared error on the y-axis. As evident from the graph, it stabilizes after 120700 iterations and does not exhibit any further decline. Hence, it can be inferred that the Particle Swarm Optimization method for 0103/0 attains the minimum squared difference between the actual Bitcoin price and the prediction.

¹² Number of function evaluation

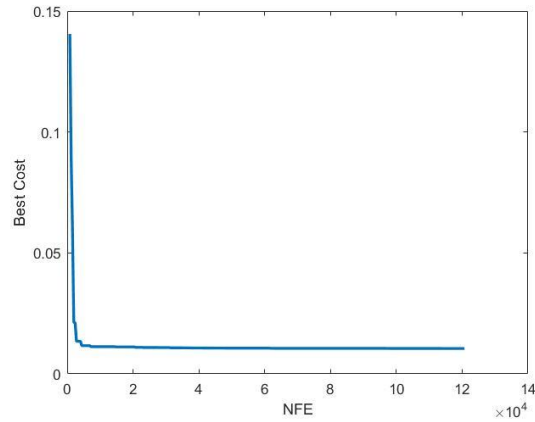


Figure 3. Particle swarm algorithm

To employ the Genetic Algorithm for prediction, we have considered a mutation rate of 3.0% and a crossover rate of 0.2%. The crossover rate is established at 8.0%. The parameters employed in the Genetic Algorithm are presented in Table 6.

Table 6. Parameters of the genetic algorithm of the training period

Varmin	Varmax	Npop	pm ¹³	mu ¹⁴
-10	+10	300	0.3	0.02

Table 7 lowest and average error in the genetic algorithm of the training course

Mean squared error (Dollar)		
Max	Average	Min
0.0111	0.0105	0.0099

As observed in Table 7, the mean squared error is 0.0105, with the minimum error value being 0.0099 and the maximum error value being 0.0111.

In the Genetic Algorithm, we have employed the Roulette Wheel Selection method, where individuals with superior fitness have a higher probability of selection. In Table 8, the mean squared error linked with the Genetic Algorithm is 0.0105, which is higher compared to the Particle Swarm Optimization algorithm. Hence, it can be concluded that the Particle Swarm Optimization algorithm outperforms the Genetic Algorithm and offers a superior solution.

Table 8. The result of the implementation of the genetic algorithm of the training course

Iteration	NFE	Mean squared error (Dollar)
250	82800	0.0105

¹³ Mutation Percentage

¹⁴ Mutation Rate

Figure 4 illustrates the mean squared error across 82800 function evaluations, which has stabilized at 0.0105 up to this iteration. As it remains relatively constant after approximately 82800 iterations, we consider 0.0105 as the mean squared error for that specific iteration.

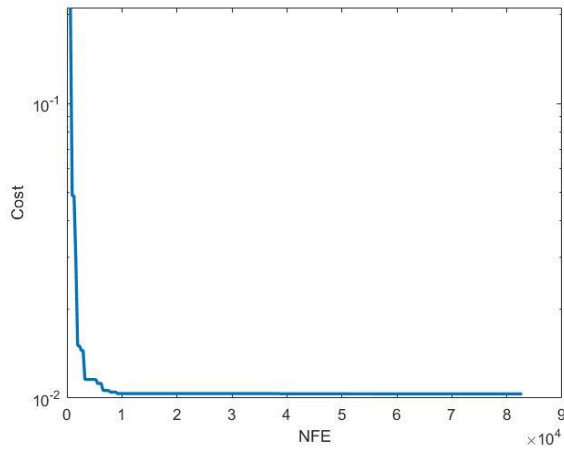


Figure 4. Genetic Algorithm

Table 9 shows the maximum, minimum, and mean squared errors obtained from the combination of Particle Swarm Optimization and Genetic Algorithm. As you can see, the errors are 0.00936, 0.00924, and 0.00921, respectively.

Table 9. Maximum, minimum and mean squared error of the combination of two algorithms (particle swarm and genetics) of the training course

Mean squared error (Dollar)		
Max	Average	Min
0.00936	0.00924	0.00921

As seen in Table 10, the mean squared error obtained from the combination of Particle Swarm Optimization and Genetic Algorithm has decreased compared to the previous two methods and has achieved better results. With 400 iterations, the calculated error using this combination is 0.00924.

Table 10. The result of the combination of two particle swarm algorithms and genetics of the training course

Iteration	Mean squared error (Dollar)
250	0.00924

In Figure 5, the x-axis represents the number of iterations, and the y-axis represents the error. As evident from the graph, the error has stabilized after 250 iterations. Therefore, the program was stopped at iteration 250, and the mean squared error is 0.00924.

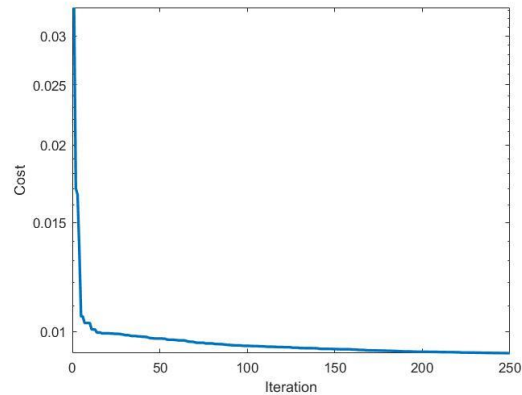


Figure 5. Combination of genetic algorithm and particle swarm

The percentage of error obtained from the combination of Particle Swarm Optimization and Genetic Algorithm is lower compared to the individual methods of Genetic Algorithm and Particle Swarm Optimization, providing a more optimal solution. Each of these algorithms has its strengths and weaknesses. The new approach of combining them aims to achieve a more efficient algorithm by leveraging their respective strengths. Therefore, by understanding the strengths and weaknesses of these algorithms, we combine them in a way that compensates for each other's weaknesses. The percentage of prediction errors for the three mentioned methods can be observed in Table 11.

Table 11. The percentage of prediction error of the training course

Algorithm used	Actual average (dollars)	Average error (\$)	percentage error
Swarm of particles	0.126	0.0102	8.13
Genetics	0.126	0.104	8.27
Combining particle swarming with genetics	0.126	0.009	7.31

After training the algorithms, we tested them with new data. Therefore, we predicted the data extracted from the beginning of 2023 until the end of September 2023 using the trained model. According to Table 12, the percentage of error in the training data and the test data does not differ significantly. Hence, it can be concluded that the trained model performs acceptably well. As observed in Table 7, the mean squared error is 0.0105, with the minimum error value being 0.0099 and the maximum error value being 0.0111.

In the Genetic Algorithm, we have employed the Roulette Wheel Selection method, where individuals with superior fitness have a higher probability of selection. In Table 8, the mean squared error linked with the Genetic Algorithm is 0.0105, which is higher compared to the Particle Swarm Optimization algorithm. Hence, it can be concluded that the Particle Swarm Optimization algorithm outperforms the Genetic Algorithm and offers a superior solution.

Table 12. The performance of the investigated algorithms during the test period

Algorithm used	Real average (trial period)	Average error (trial period)	Error percentage (training period)	Error percentage (trial period)
Swarm of particles	0.5327	0.040	8.13	7.67
Genetics	0.5327	0.047	8.27	8.84
Combining particle swarming with genetics	0.5327	0.039	7.31	7.47

5 Comparison and Analysis of Results

Bitcoin, as a digital currency, has two fundamental applications: as a form of money and as a tool for value transfer. Individuals can use it to purchase goods and services, enabling them to acquire the items they need. Additionally, Bitcoin can serve as a store of value, similar to gold. By acquiring it, individuals can preserve the value of their assets and safeguard against inflation.

Bitcoin has experienced significant price fluctuations since its inception. While some of these fluctuations can be attributed to factors discussed in this research, there are other uncontrollable factors, such as news related to the cryptocurrency. Negative news can cause a decrease in the price of Bitcoin, while positive news can cause an increase. Given that the cryptocurrency market has no limitations on its fluctuation range, this adds to the market risk and it is possible for a cryptocurrency to experience a price drop of up to 98% in less than 24 hours. The value of a cryptocurrency depends on its investors; therefore, it can be said that a cryptocurrency does not have intrinsic value, and all its value is based on the trust of its investors. In contrast, gold possesses intrinsic value as it is a valuable and rare metal used in various industries. However, in the age of information technology, cryptocurrencies have the potential to revolutionize transactions and business. Consider the difficulty involved in transferring fiat money or gold from one distant point to another country. Cryptocurrencies eliminate this challenge, allowing for the instant transfer of desired amounts of money without the need for intermediary institutions such as banks. Moreover, this can be done at any time, day or night.

The previous studies were mostly conducted using deep learning techniques and neural networks, which have proven to be effective in short-term Bitcoin price prediction. However, these studies did not consider all the influential factors on Bitcoin price together. Additionally, practical algorithms such as genetic algorithms and particle swarm optimization were not utilized. In this research, we identified and analyzed the factors that routinely impact cryptocurrency prices. These factors include the S&P 500 index, gold, the Dow Jones index, the consumer price index, and the dollar index. We obtained the price variations of these indices from the emergence of Bitcoin until the end of 2022.

"The important factor that we considered in this research was the impact of these factors on the price of Bitcoin. Determining the weighting of these factors is not simple, as many factors influence its price. Therefore, in this study, we identified the important and major factors and obtained optimal coefficients for them. According to Table 13, the impact of each factor on the price of Bitcoin is evident.

Table 13. Calculation table of optimal coefficients

Variables	Average optimal coefficients
Dollar index	-4.56
Inflation	4.06

Consumer index	2.27
S&P500	-1.55
Dow Jones index	0.14
Gold	0.05

For example, the highest impact is from the US Dollar index, followed by the inflation rate and gold. Gold has the least effect on Bitcoin. Table 14 shows the comparison of the execution results of the algorithms. The number of input variables for all three algorithms is 6. The Particle Swarm Optimization algorithm has a population size of 200, while the other two algorithms have a population size of 300. This indicates the strong performance of the Genetic Algorithm in searching for solutions. As you can see in the table, the combination of these two algorithms has yielded better results.

It was determined in this research which factor has had the most significant impact on the price of Bitcoin since its inception until now. Therefore, the US Dollar index has been assigned the highest coefficient. The inflation rate and consumer price index follow in rank.

Table 14. Comparison of the results of the training period algorithms

Algorithm type	Mean squared error	Variable number	The number of repetitions	Number of population	Error percentage in prediction
Particle swarm algorithm	0.103	6	300	200	8.13
Genetic algorithm	0.0105	6	250	300	8.27
Combination of particle swarm algorithm and genetic algorithm	.00924	6	250	300	7.31

6 Discussion and Conclusion

6.1 Significance of Indicators

In this study, we concluded that the dollar index has the most significant impact on the price of Bitcoin, followed by the inflation rate and the consumer index. The significance of these indicators can vary over time, meaning that factors currently influencing the price of Bitcoin may be replaced by new factors in the future. In fact, the influence of these factors is somewhat dynamic. It is even possible that their effect on the price of Bitcoin may change. For example, a variable that currently has a positive effect on the price of Bitcoin may have a negative effect in the future, such as the inflation rate, which according to this research, had a positive impact on the price of Bitcoin in the past but now has a reversed effect.

With an increase in inflation, the Federal Reserve raises interest rates, which attracts investors towards low-risk assets and away from high-risk markets like Bitcoin. However, it should be noted that Bitcoin's susceptibility to these influences is gradually decreasing over time.

6.2 The best method for prediction

The best method for prediction in this study is the one with the lowest mean squared error. Regarding the algorithms, it should be noted that the combination of two algorithms has the highest efficiency with a prediction

error rate of 7.3. The particle swarm algorithm follows with 8.13, and finally, the genetic algorithm with 8.27. Therefore, the best method is the combination of the particle swarm and genetic algorithms.

6.3 The conclusion:

The approach in this research has been fundamental, considering what the future of Bitcoin will be. It is certain that throughout history, humans have resisted changes but ultimately had to accept and adapt to them. For example, when the Internet became a global phenomenon, there was opposition, but now almost everyone uses it in some form. If we consider Bitcoin as a major change in the global society, it will undoubtedly face opposition, most of which comes from governments, institutions, and central banks. However, Bitcoin has successfully overcome their resistance over the past few years and has established its position. Bitcoin will undoubtedly transform the future of the global economy. With the advantages that Bitcoin offers, it will find its place in the global economy and replace fiat currencies in the not-so-distant future. Currently, many countries use it to circumvent sanctions and have, in a way, accepted it, although they have not officially announced it. The first country to take a step forward in this regard and adopt Bitcoin as its national currency, paying its citizens with Bitcoin, was El Salvador in South America. In the future, other countries will join El Salvador. Furthermore, governments show less resistance to Bitcoin as soon as they find a way to control digital currencies. At the time of conducting this research, the cryptocurrency market is valued at over \$1.25 trillion, which is evidence of Bitcoin's strength. One of the factors that has a significant impact on digital currencies and is uncontrollable is the news that is published. If this news is positive, it will increase the price, and if it is negative, it will lower the price. In fact, the intrinsic value of digital currencies is based on the capital that enters them. This is why digital currencies are highly risky for investment.

6.4 Suggestions and Limitations:

The suggestion for future research at the end of this study is to investigate the impact of news on digital currencies, as well as to examine the laws of governments and their influence on digital currencies. Furthermore, it is recommended to carefully examine the limitations that must be observed when using cryptocurrencies, including security issues, price volatility, and legal and financial restrictions. Additionally, it is advised to conduct thorough research before investing in the cryptocurrency market and carefully assess the associated risks of investment in this market.

References

- [1] Amirhosseini, Z., Davarpanah, A. (2016). A Model Designed to Predict the Price of Gold Using particle swarm optimisation and Genetic Algorithms and Providing Combined Algorithm.
- [2] Arias-Oliva, M., Pelegrin-Borondo, J., Matias-Clavero, G. (2019). Variables influencing cryptocurrency use: a technology acceptance model in Spain. *Frontiers in psychology*, 10, 475.
- [3] Bunjaku, F., Gjorgieva-Trajkovska, O., Miteva-Kacarski, E. (2017). Cryptocurrencies—advantages and disadvantages. *Journal of Economics*, 2(1), 31-39.
- [4] Chen, J. (2023). Analysis of bitcoin price prediction using machine learning. *Journal of Risk and Financial Management*, 16(1), 51.
- [5] Cohen, G. (2020). Forecasting bitcoin trends using algorithmic learning systems. *Entropy*, 22(8), 838.
- [6] Dash, M. (2020). Analysis of Bitcoin Returns Volatility using AR-GARCH Modelling. Available at SSRN 3567216.
- [7] Faghieh Mohammadi Jalali, M., Heidar, H. (2020). Predicting changes in Bitcoin price using grey system theory. *Financial Innovation*.

- [8] Guo, T., Bifet, A., & Antulov-Fantulin, N. (2018, November). Bitcoin volatility forecasting with a glimpse into buy and sell orders. In 2018 IEEE international conference on data mining (ICDM) (pp. 989-994). IEEE.
- [9] Hamayel, M. J., Owda, A. Y. (2021). A novel cryptocurrency price prediction model using GRU, LSTM and bi-LSTM machine learning algorithms. *Ai*, 2(4), 477-496.
- [10] Hattori, T. (2020). A forecast comparison of volatility models using realized volatility: Evidence from the Bitcoin market. *Applied economics letters*, 27(7), 591-595.
- [11] Jiang, X. (2019). Bitcoin price prediction based on deep learning methods. *Journal of Mathematical Finance*, 10(1), 132-139.
- [12] Khedmati, M., Seifi, F., Azizi, M. J. (2020). Time series forecasting of bitcoin price based on autoregressive integrated moving average and machine learning approaches. *International Journal of Engineering*, 33(7), 1293-1303.
- [13] Li, M. (2021, December). Prediction of bitcoin price based on the hidden markov model. In 2021 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021) (pp. 2962-2967). Atlantis Press.
- [14] Maleki, N., Nikoubin, A., Rabbani, M., Zeinali, Y. (2023). Bitcoin price prediction based on other cryptocurrencies using machine learning and time series analysis. *Scientia Iranica*, 30(1), 285-301.
- [15] Mehta, P., Sasikala, E. (2020). Prediction of Bitcoin using recurrent neural network. *Int J Recent Technol Eng (IJRTE)*, 8(6), 1303-7.
- [16] Mirghfour, S.H., Sayadi, H., Dehghani Zadeh, N. Advantages and disadvantages of digital currencies with an emphasis on Bitcoin. www.SID.ir. (In Persian).
- [17] Mohammadsharifi, A., Kahlili-Damghani, K., Abdi, F., & Sardar, S. (2021). Predicting the Price of Bitcoin Using Hybrid ARIMA and Deep Learning. *Industrial Management Studies*, 19(61), 125-146.
- [18] Monadjemi, S. A., Abzari, M., Rayati Shavazi, A. (2009). Modeling of Stock Price Forecasting in Stock Exchange Market, using Fuzzy Neural Networks and Genetic Algorithms. *Quarterly Journal of Quantitative Economics*, 6(22).
- [19] Mousavi, S.S., Fatemi, S., Akbari, H., Meshkat, S.R. (2010). Optimization by population-based meta-heuristic. Maybod University, first edition, first edition, 1389.
- [20] Mozaffari, M. A., Bajalan, S., Eivazlu, R. (2022). Analyzing the volatility behavior of Bitcoin and examining its safe haven and hedge capability for Iranian investors. *Journal of Financial Management Perspective*, 12(37), 9-35.
- [21] Munim, Z. H., Shakil, M. H., Alon, I. (2019). Next-day bitcoin price forecast. *Journal of risk and financial management*, 12(2), 103
- [22] Naghipour, H., Nabavi Chashmi, A., Barzegar, B., Memarian, E. (2023). Modeling and prediction of bitcoin prices based on blockchain information. *International Journal of Nonlinear Analysis and Applications*, 14(1), 1601-1610.
- [23] Poongodi, M., Vijayakumar, V., & Chilamkurti, N. (2020). Bitcoin price prediction using ARIMA model. *International Journal of Internet Technology and Secured Transactions*, 10(4), 396-406.
- [24] Ravi, C. (2020). Fuzzy crow search algorithm-based deep LSTM for bitcoin prediction. *International Journal of Distributed Systems and Technologies (IJDST)*, 11(4), 53-71.
- [25] Sanchez Ascanio, L. C. Arredondo Garcia, J. A. (2020). Predicting the Price of Bitcoin, and more. *Suma de Negocios*, 11(24), 42-52.
- [26] Sharifi, A., Khalili Damghani, K, A., Abdi, F., Sardar, S. (2021). Bitcoin price prediction using ARIMA combination model and deep learning. *Industrial Management Studies Quarterly*, 19(61).
- [27] Shokri, N., Sahab, M. (2021). Investigating the effects of financial volatility spillover between digital currencies (application of multivariate GARCH approach). *Journal of Financial Management Perspective*, (35), 143-172.
- [28] Wardak, A. B., Rasheed, J. (2022). Bitcoin cryptocurrency price prediction using long short-term memory recurrent neural network. *Avrupa Bilim ve Teknoloji Dergisi*, (38), 47-53.
- [29] Zhang, S., Li, M., Yan, C. (2022). The empirical analysis of bitcoin price prediction based on deep learning integration method. *Computational Intelligence and Neuroscience*, 2022(1), 1265837.
- [30] Zhu, Y., Dickinson, D., Li, J. (2017). Analysis on the influence factors of Bitcoin's price based on VEC model. *Financial Innovation*, 3, 1-13.